A Markov Model for Temporal Dominance of Sensations (TDS) data

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Introduction

- This poster presents a method for modelling temporal dominance of sensations (TDS; Pineau, Cordelle & Schlich, 2003) data for six flavour fresh consumer cheese products (Thomas et al., 2014). TDS data are collected through the identification of a single dominant attribute (DAs; Table 1), which is updated over time.

Table 1: DAs: full names and coding.

Dominant Attribute	Coding
Cream	C
Salty	Sa
Garlic	G
Pungent	Pu
Fresh Herbs	FH
Cooked Herbs	CH
Sour	So
Pepper	Pe
Start	St
Stop	Sp

- TDS data are tokenized into TDS dyads, where each dyad represents the transition from one attribute to another. These transitions can be illustrated in a number of ways, e.g., consider the path given in Figure 1.

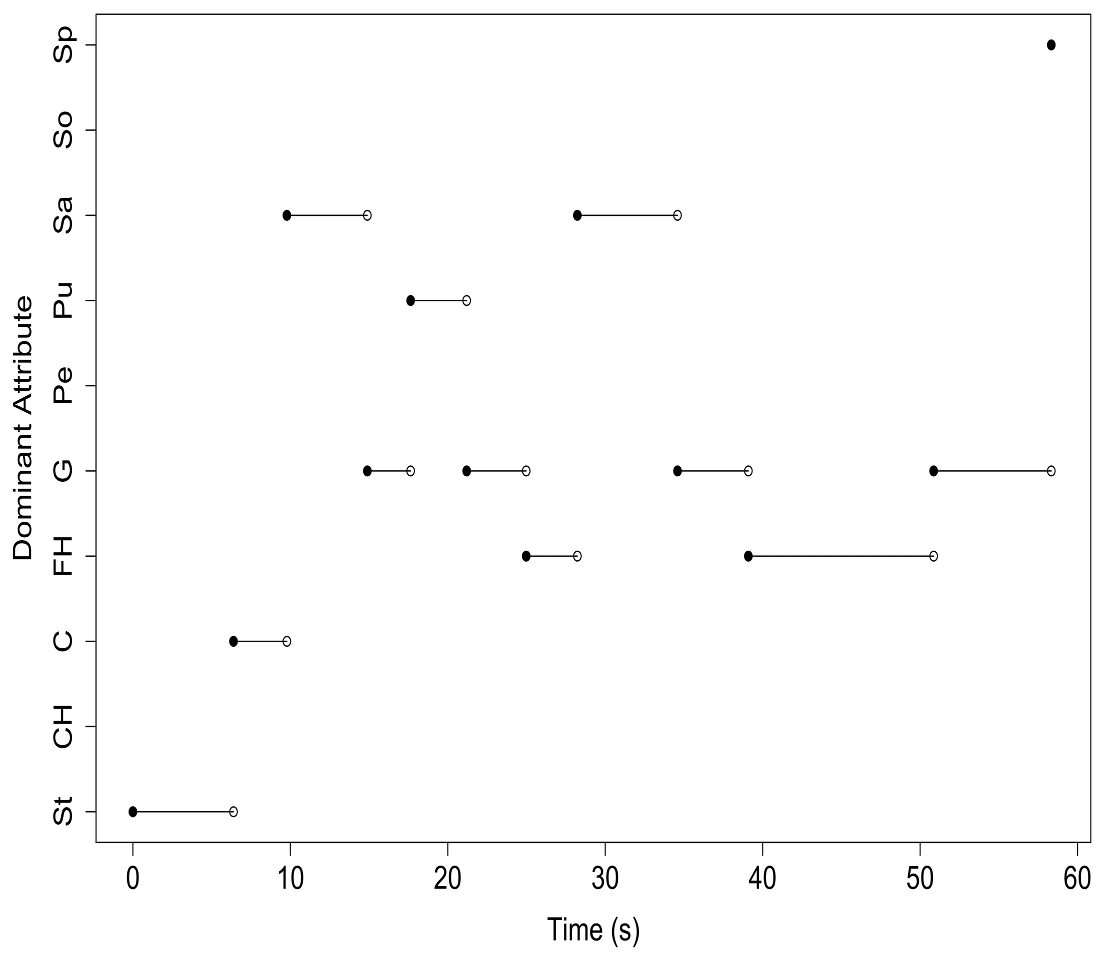

Figure 1: An illustration depicting a random assessors' experience while evaluating the first product.

Methodology

- We propose to model the observed systems of TDS dyads using a discrete-time Markov chain that adheres to the Markovian property. Under these assumptions we arrive at a time-homogeneous model that states

$$P\{X_{t+1} = j \mid X_t = i\} =: p_{ij},$$

where

- X_t represents the DA being experienced at time t,
- each $p_{ij} \geq 0$, for $i, j \in D$, is a transition probability,
- the $\sum_{j \in D} p_{ij} = 1$, for $i \in D$, and
- D is the state space containing all DAs.

- This framework can, among other things, allow us to make predictions about which DA may be experienced at a future time point given a assessor is experiencing a DA at time t.

Results

- For each flavour fresh cheese, we construct a transition matrix $\mathbf{P}_k$, for $k = 1, \ldots, 6$. Each transition matrix gives the probability of moving from one DA to another. We use each $\mathbf{P}_k$ to create a Markov chain. Figure 2 displays an "accented" Markov chain for Product 1.

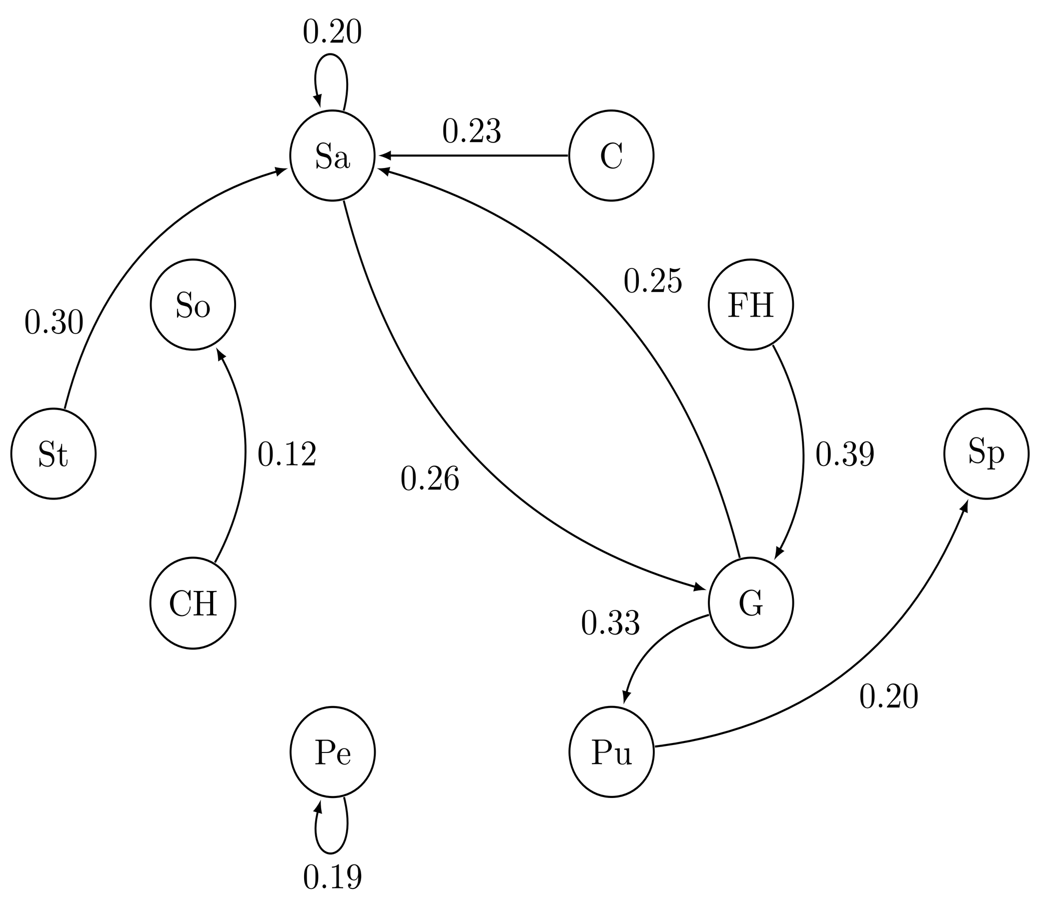

Figure 2: An accented Markov chain for the first flavour fresh cheese. The given values highlight the most popular transitions among the 63 assessors who evaluated this product.

- The accented Markov chain in Figure 2 is reducible among the eight DAs. This is consistent with $\mathbf{P}_1$, which indicates no assessor transitioned from CH to FH. Interestingly, this is the only product that has this property.
- For Product 1, the most popular transition is from G to Sa. Similarly, the transition matrices for Products 2 – 5 also indicate that G is a commonly selected DA. Unlike these products, $\mathbf{P}_6$ indicates that CH was the most popular DA for this attribute. Figure 3 displays an accented Markov chain for Product 2.

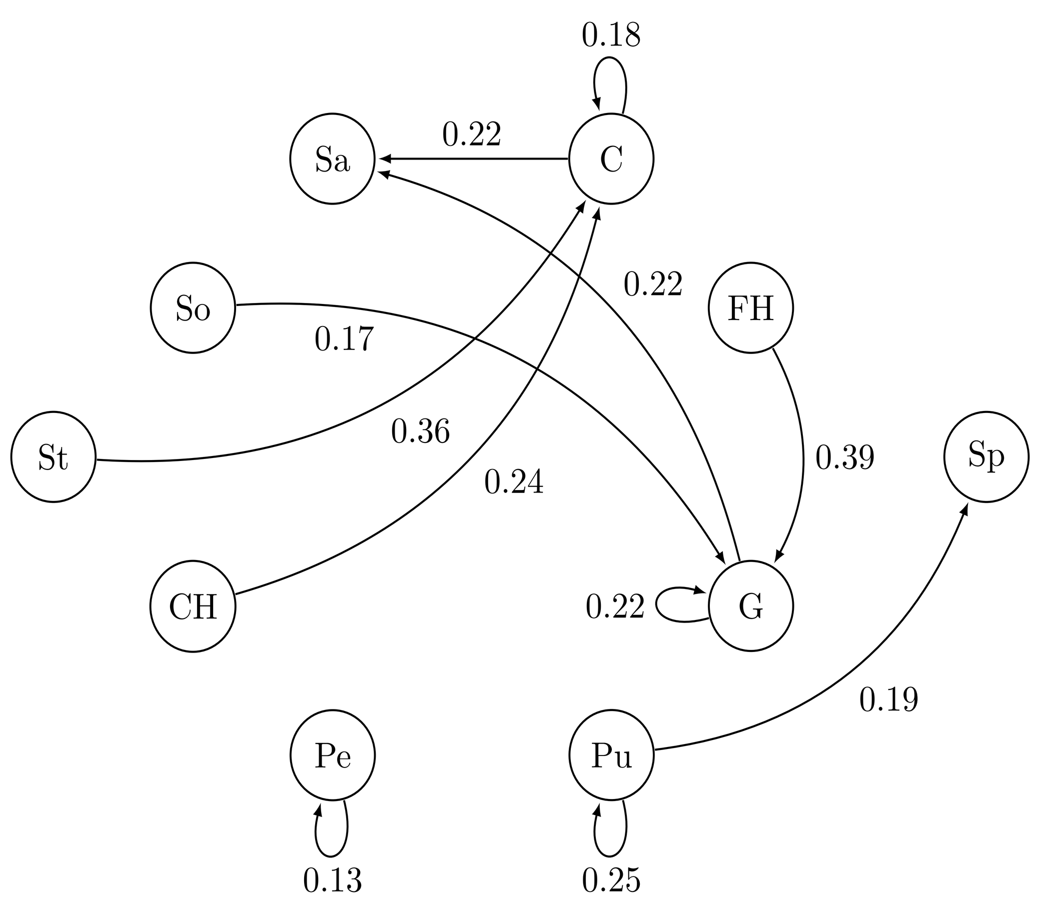

Figure 3: An accented Markov chain for the second flavour fresh cheese. The given values highlight the most popular transitions among the 63 assessors who evaluated this product.

- Figure 3 shows that C was oft-times selected. It also demonstrates another common trend; for every Product, aside from 5, once the assessor selected Pu, the most common transition was to Sp.
- This feature, along with a number of other similarities is highlighted in Figure 4, which displays an accented Markov chain for Product 6.

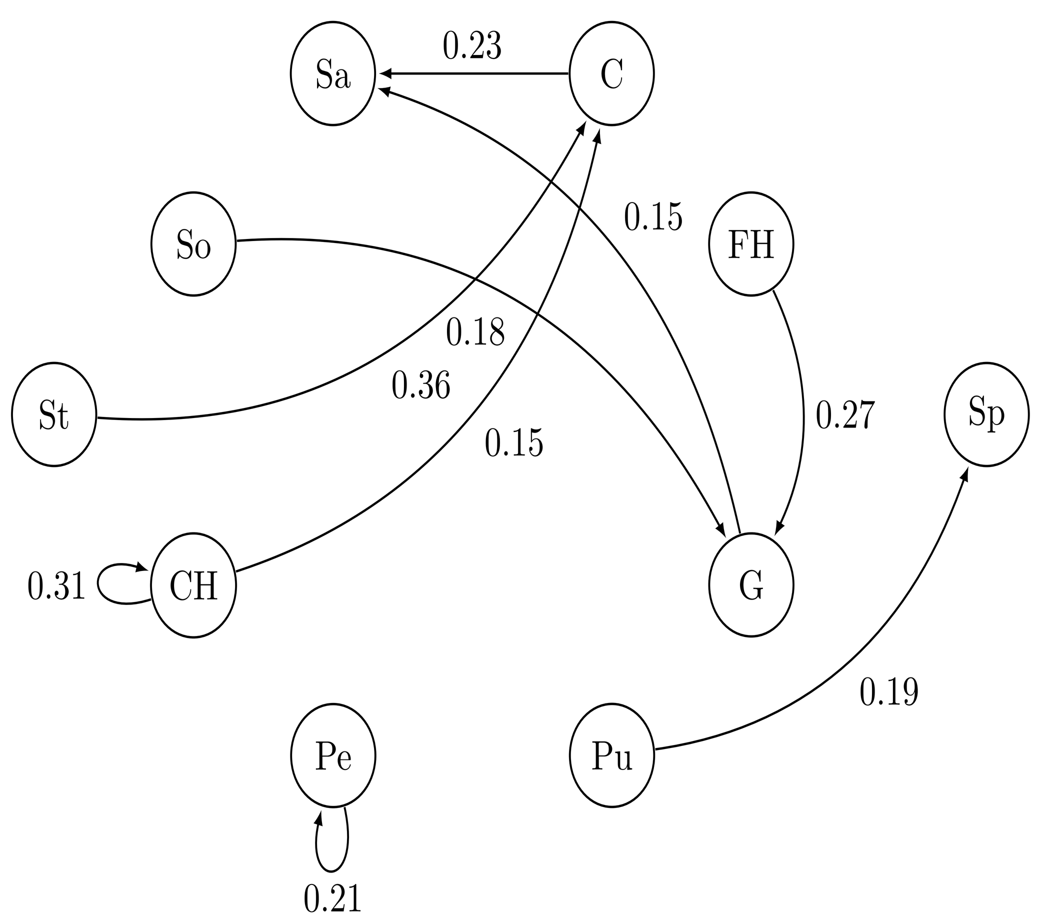

Figure 4: An accented Markov chain for the sixth flavour fresh cheese. The given values highlight the most popular transitions among the 63 assessors who evaluated this product.

- We can use each transition matrix to make predictions about future time points. For example, Table 2 gives the transition probabilities between time t and $t+1$ associated with an assessor evaluating Product 1 who is experiencing Sa at time t.

Table 2: At time $t{+}1$, the p_{ij} for a assessor evaluating Product 1 and experiencing S at time t.

	CH	C	FH	G	Pe	Pu	Sa	So	Sp
p_{ij}	0.05	0.06	0.09	0.25	0.08	0.05	0.20	0.09	0.12

- Table 2 indicates that the most likely transition from S at time t would be to G at time $t+1$. This result is consistent with the trends observed in $\mathbf{P}_1$ and displayed in Figure 2.
- Table 3 gives the transition probabilities at time $t+3$ associated with an assessor evaluating Product 1 who was experiencing Sa at time t.

Table 3: At time $t{+}3$, the p_{ij} for a assessor evaluating Product 1 and experiencing S at time t.

	CH	C	FH	G	Pe	Pu	Sa	So	Sp
p_{ij}	0.03	0.05	0.08	0.18	0.05	0.06	0.14	0.05	0.11

- Like Table 2, Table 3 indicates that it is most likely that at time $t+3$ this assessor will experience G. Otherwise, the assessor may continue to experience S or will stop evaluating this product.

Conclusions

- For every Product, G was selected quite often. This result provides some support for a conclusion given in Castura & Li (2015), who identified G as a positive Hedonic driver.
- This poster discussed a novel way for modelling TDS data. Future work will include a study of continuous time Markov models and log-linear models to incorporate information regarding the amount of time spent experiencing each DA.

Acknowledgements

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